The presence of academic journals on Twitter and its relationship with dissemination (tweets) and research impact (citations)

José Luis Ortega

Cybermetrics Lab, Madrid, Spain, jortega@orgc.csic.es

Purpose: This paper analyses the relationship between dissemination of research papers on Twitter and its influence on research impact.

Design/methodology/approach: Four types of journal Twitter accounts (journal, owner, publisher and no Twitter account) were defined to observe differences in the number of tweets and citations. 4,176 articles from 350 journals were extracted from Plum Analytics. This altmetric provider tracks the number of tweets and citations for each paper. Student's t-test for two-paired samples was used to detect significant differences between each group of journals. Regression analysis was performed to detect which variables may influence the getting of tweets and citations.

Findings: Results show that journals with their own Twitter account obtain more tweets (46%) and citations (34%) than journals without a Twitter account. Followers is the variable that attracts more tweets (β=.47) and citations (β=.28) but the effect is small and the fit is not good for tweets (R^2=.46) and insignificant for citations (R^2=.18).

Originality/value: This is the first study that tests the performance of research journals on Twitter according to their handles, observing how the dissemination of content in this microblogging network influences the citation of their papers.

Keywords:

Webometrics; Twitter; Altmetrics; Research journals; Plum Analytics

1. Introduction

Twitter has recently become one of the most important media for information diffusion in the digital world. On this platform, users can spread their ideas and opinions, promote their results and discuss with millions of other users just using short and direct messages. The success of the site lies in the ability of following and being followed, which creates a dense network of contacts that forward and reply the received messages. This yields a huge and constant information flow, where any trivial post may shortly become trending topic (Murthy, 2013). Twitter has hence become an important way to spread research advances and to popularize the academic activity of scientists and organizations. In this form, authors and universities use Twitter more and more to share their academic outputs with other colleagues and to maintain a digital presence that brings them visibility and prestige (Mahrt et al., 2014).

In this context, the academic publishing industry has played a critical role as disseminator of scientific results because it has traditionally been the only mediator between authors and readers. Until the 21st century, journals were the main vehicle for distributing research papers, ensuring the worldwide spreading of scientific results. The prestige of these venues (i.e. Impact factor, peer-review) increased the number of subscriptions and therefore reached more academic readers. Now, the World Wide Web and social networking sites are occupying a prime place in the promotion and dissemination of research results, where research articles acquire a prominent position to the detriment of academic journals (Phillips, 2010). In this new communication environment, journals need to redefine their role in the spreading of scientific results. Whether they maintain the same importance or, on the contrary, they fall in value. This paper thus explores the importance of journals in the dissemination of their research papers in online social network and how this diffusion has influence on the citation impact of these same articles.

New metrics and indicators from online social networks and other Web 2.0 environments are being suggested as proxies or alternative measures for research evaluation (Piwowar, 2013). Altmetric providers (e.g. Altmetric.com, Plum Analytics) and academic publishing houses (e.g. Nature Publishing Group, PLOS) are counting the number of tweets and retweets that mention research papers. These metrics are being used as indicators of social recognition or even as a way to detect early scientific impact. However, this is causing uneasiness in the scientific community, given the possibility that these metrics may be used for research assessment before to be tested and analysed (Thelwall et al., 2013). Due to this, it is necessary to understand the true meaning of these measures, specifically the number of tweets. In addition, it is necessary to disclose in which way the promotional activities of journals could affect the research impact of their articles.

2. Related Research

Since the launch of Twitter, many studies appeared describing the service and its impact in the web (Java et al., 2007; Huberman et al., 2008), while other ones explored the potential of this network from an educational (Grosseck & Holotescu, 2008), sociological (Ryan, Hazlewood & Makice, 2008) or business (Geho, Smith & Lewis, 2010) view. The possibilities of this microblogging service for the dissemination of scholarly results were also analysed (Gruzd, 2012; Kim et al., 2012). Results suggested new ways of scientific communication, mainly regarding to the attendance of scientific conferences (Letierce et al., 2010; Chen, 2011; Weller et al., 2011).

The advent of altmetrics caused that many scholars sensed that there was some connection between tweets and citations. This idea encouraged scientists to carry out new studies on the meaning of that relationship for research evaluation. Eysenbach (2011) extracted 1,573 tweets that mentioned *Journal of Medical Internet Research*'s articles, finding that tweets can predict highly cited papers within the first 3 days of publication. Shuai et al. (2012) analysed the Twitter mentions to 4,606 pre-prints in

Arxiv.org and they detected significant correlations between tweets and early citations. Thelwall et al. (2013) unexpectedly detected a negative correlation between tweets and citations, provoked perhaps by the fast increase of mentions on Twitter in front of the usual time delay of citations. In one of the most comprehensive studies, Haustein et al. (2014) analysed tweets to 1.4 million research papers from Pubmed. The correlation between tweets and citations was small and rather different according to disciplines and journals. Another similar study explored 20,000 publications from Web of Science using Principal Component Analysis. Their authors found that tweets and citations formed different components (Zahedi et al., 2014). De Winter (2015) studied the citation impact of *PLOS One*'s papers and noticed that tweets were better predictors of citations than other altmetrics measures. More recently, Tonia et al. (2016) did not detect statistical differences between tweeted and non-tweeted papers according to the number of citations. And Yu (2017) found that tweets from scholarly users better correlate with citations.

Focusing on the possibilities of Twitter for research dissemination and its meaning for scholarly impact, several studies have explored how research articles are mentioned and spread through Twitter. Andersen and Haustein (2015) distinguished the most tweeted medical papers (clinical trials, reviews and meta analyses) and demonstrated that those articles are the most followed by the general public. Tsou et al. (2015) carried out a demographic study of the profiles that mentioned research articles. They found that most are males with doctoral degrees and concluded that the mention of research papers on Twitter is mainly done by the scholarly world. Na (2015) analysed the content of the tweets that referred to research papers and he found that more than 52% of tweets summarize the main findings of the study. Ortega (2016) observed that authors registered on Twitter improved the visibility of their papers and in consequence the likelihood of increasing the number of citations.

Literature on the specific role of journals on Twitter and their importance in the dissemination and impact of research articles is scant. Many of these studies are about the presence and performance of academic journals on Twitter but in specific disciplines (Boulos and Anderson, 2014; Nason et al., 2015). Zhao and Wolfram (2015) found moderate correlation between the Twitter mentions and Eigenfactor score for Library and Information Science journals. Kelly et al. (2016) discovered that radiology journals with Twitter handles have higher Impact Factors than those without handles, and the number of followers of a journal's Twitter profile is positively associated with Impact Factor. Bornmann and Haunschild (2016) suggested a normalization of journal mentions based on quartiles. However, no papers have been noted which discuss the importance of different Twitter profiles of journals for the dissemination and impact of research papers.

3. Objectives

The aim of this paper is to observe how the presence of journals on Twitter could promote the diffusion of their articles in this digital platform and to measure the relationship of this activity with the research impact of scientific papers. Several research questions were formulated to address this purpose:

- Which is the best way for journals to participate in Twitter? Using its own account or through the owner or publisher account?
- Are articles published in journals registered in Twitter more tweeted than papers from journals without a Twitter account?
- Are articles from journals with a Twitter presence more cited than papers from journals not registered in this social network?
- What Twitter account metrics (i.e. total tweets, followers, followings, etc.) of a journal have more influence on the citation impact and the mention of their documents on Twitter?

4. Methods

4.1. Data Sources

Plum Analytics: Plum Analytics is a provider of alternative metrics (Champieux, 2015; Lindsay, 2016). This means this platform extracts data from secondary sources (e.g. social networks, repositories, publishing platforms, etc.), describing the performance of the same document in different online environments. Created in 2012 by Andrea Michalek and Michael Buschman, it presents the advantage that their data can be aggregated by author or organization. This allows the service to present graphics and statistics on the online impact of researchers, departments and universities. This service was selected because it offers an easy way to extract information from authors and documents. Plum Analytics offers a suitable coverage of Twitter data because it employs, since April 2016, Gnip, the official data provider of Twitter. In addition, this provider uses several identifiers to extract mentions to documents (not only DOI). Another important advantage is that Plum Analytics makes public web pages for organizations where the altmetric information of their authors and publications is freely available (e.g. https://plu.mx/pitt/g/).

Twitter: Created in 2006, Twitter is the most popular microblogging service around the world and it could be considered one of the most important online instruments for promoting oneself and sharing information and opinions. In Twitter, users can send short messages to a general audience shaped by other members (followers) interested in their opinions and activities. At the same time, users also follow other Twitter members (followings) who, through their messages, provide them with relevant information. In this way, Twitter has become a global channel of information exchange and an interesting way to spread academic results. Twitter was selected due to several reasons. Firstly, this is the most important web tool to spread information. Secondly, the number of tweets that a document receives is being counted by all the altmetric providers (Altmetric.com, ImpactStory, Plum Analytics, etc.) as a measure of societal impact; and thirdly, the mention of research papers on Twitter is currently a hot topic in scientometric and altmetric studies.

4.2. Data extraction

Plum Analytics does not present aggregated information at journal level. Therefore, information about research papers was extracted from institutional profiles. For this purpose, public institutional profiles created by that provider were searched in Google (site: plu.mx). Institutional profiles of the Georgia Southern University, St. Mary's College of California, University of South California and University of Pittsburgh were found and used to extract author profiles. In addition, authors from different institutions were gathered from the generic web page of Plum Analytics (https://plu.mx/plum/g/). A total list of 1,097 author profiles was retrieved. 62,874 items were gathered from the retrieved authors. This procedure guarantees the randomness of the sample and avoids disciplinary biases. This randomness is demonstrated by the Runs test, showing that the means of Tweets (p-value=.398), Total Tweets (p-value=.959), Citations (p-value=.967) and Followers (p-value=.409) are similar to a random sample. Data were obtained during April 2016.

350 journals with the largest number of papers indexed in Plum Analytics were considered in this study. 4,176 research articles published in 2013 from those journals were selected from the main sample so every article has the same time window. It was considered that during three years, a paper would receive most of their citations and tweets.

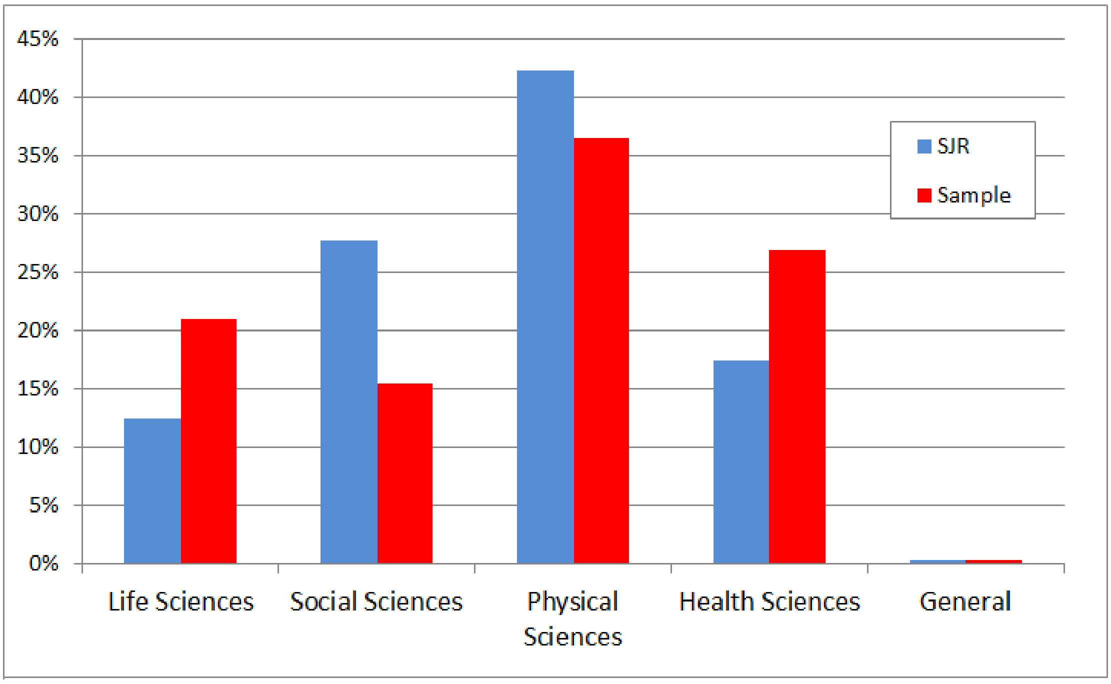

Figure 1. Comparative distribution of journals by disciplines within the sample and the Scimago Journal Rank.

Figure 1 presents the distribution of journals by subject areas both in the sample and in the Scimago Journal Rank (www.scimagojr.com/). The chart shows that there is a slight disciplinary bias toward Life Sciences and Health Sciences journals. It is unknown at what extent these shifts can influence the results, because no disciplinary differences have yet been observed in the use of Twitter by journals. Despite this, these differences will be considered when the results are discussed.

Information on whether one journal has or does not have a Twitter account was manually extracted from Twitter. First, the journal's home page was explored to obtain references or links to its own Twitter account. If there is not a link to a Twitter account, the platform was searched to locate any handle related to the journal. In the case that no accounts were found, the Twitter accounts of their owners or publishers were searched. In this way, 350 journals were classified according to four possibilities[1]:

- **Journal account**: This category groups journals with their own Twitter account. For example, *The Lancet* has the profile *@TheLancet*, used to post only information on the journal itself. 101 (29%) journals have their own account.
- **Owner account**: This group contains journals without a Twitter account but whose owners do have one. Owner is defined as the holder of the journal, but not its publisher. Often these journals belong to a society, organization or university, but the publishing activity is transferred to a publishing house. For example, *Journal of Pediatric Orthopaedics* is property of the *Pediatric Orthopaedic Society of North America (POSNA)* and published by *Wolters Kluwer*. Here, the owner's twitter account is selected to represent the journal because one might suppose that this account may be used for publicizing the journal. 76 (22%) journals are grouped in this category. In the event that the owner is also the publisher (e.g. *Journal of Nuclear Medicine* is owned by the *Society of Nuclear Medicine and Molecular Imaging (SNMMI)* and published by the same organization), the journal is classified as Owner account because the role of that organization is closer to the owner activity than the publisher one.
- **Publisher account**: When a journal does not have neither its own account nor the owner is registered on Twitter, then the Twitter account of the publisher is selected. Large publishing houses (i.e. *Elsevier*, *Wiley*, *Springer*) have specific accounts that promote the content of journals according to research areas. For example, *Elsevier* has *@MaterialsToday* for journals on Material Science, *@ElsevierEnergy* for Energy journals and so on. 103 (29%) journals are included under this category.
- **No Twitter account**: This category groups journals that are not present on Twitter under any of the above mentioned types of accounts. In this way, neither

[1] The list of journals and the classification result can be downloaded here: https://www.researchgate.net/profile/Jose_Ortega7/publication/316189052_journals_list_by_Twitter_account_type/data/58f5bdadaca27289c21cd97d/journal-list.xlsx

publishers nor owners are registered on Twitter. Only 70 (20%) journals were not represented on Twitter.

Data about each Twitter account was normalized by year because it is more probable that old accounts display more activity than the newest ones. Due to these differences, the activity of each account (number of tweets, retweets, followers and followings) was divided by the number of years from the creation date to April 2016. For example, the Twitter account of the *Journal of the Acoustical Society of America* was created in December 2009, 7.17 years ago in April 2016. Then, the number of Tweets per year results from 14,978 tweets divided by 7.17 years, 2,088 tweets per year. This normalization was also applied to citations to make possible the comparison with tweets., Only Twitter accounts created before 2013 were analysed because this study only considers articles published during that date. In this way, it is possible to measure the impact of journal Twitter accounts in the life cycle of research articles.

4.3. Statistics

All the variables were transformed to logarithmic scale (ln(1+x)) to acquire a normal distribution. In this way, it is possible the utilization of parametric statistics, more powerful than the non-parametric ones.

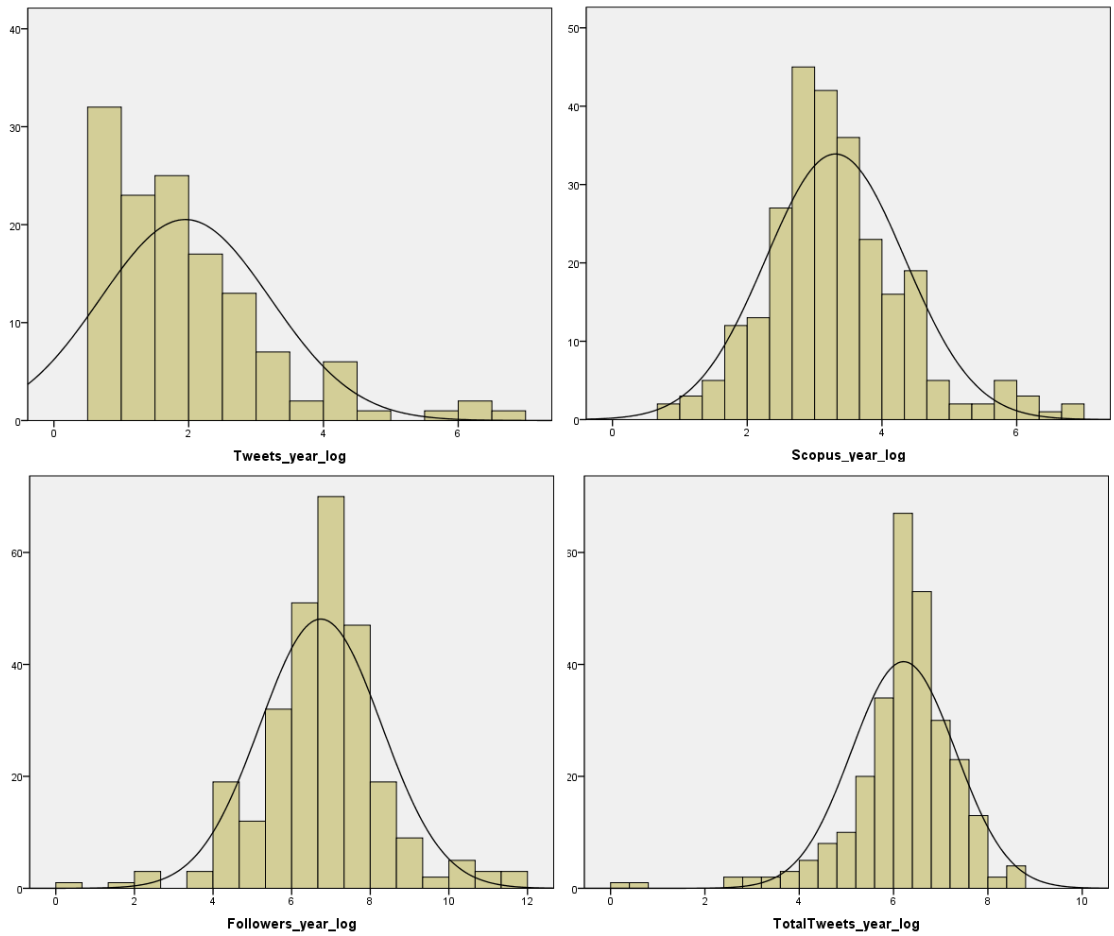

Figure 2. Assumption of normality of the transformed variables.

Figure 2 depicts the histogram of the variables used in this study. They follow a normal distribution after the log transformation. Only *Tweets_year_log* maintains a slight skewness, which suggests certain caution when it comes to interpret the value of the mean.

Two statistical analyses were conducted to answer the formulated questions:

Student's t-Test for independent samples: This test was used to compare the means of the sub-samples (i.e. journal, owner, publisher, not on Twitter). T-test assumes normality of the variables and is suitable for small samples. In addition, it allows checking the differences between means and establishing confidence intervals for them.

Regression analysis: This technique was utilised to estimate the influence of Twitter account metrics (total tweets, followers, followings, etc.) on the number of tweets and citations that articles receive. Simple regression analysis was performed because these variables are not independent among them.

5. Results

Results of this study are presented in three sections. The first one describes the differences between journal Twitter accounts and the number of tweets that their articles receive.

5.1. Differences between journal Twitter accounts

This section shows the differences between journal Twitter accounts according to the number of Twitter mentions and citations that their articles receive.

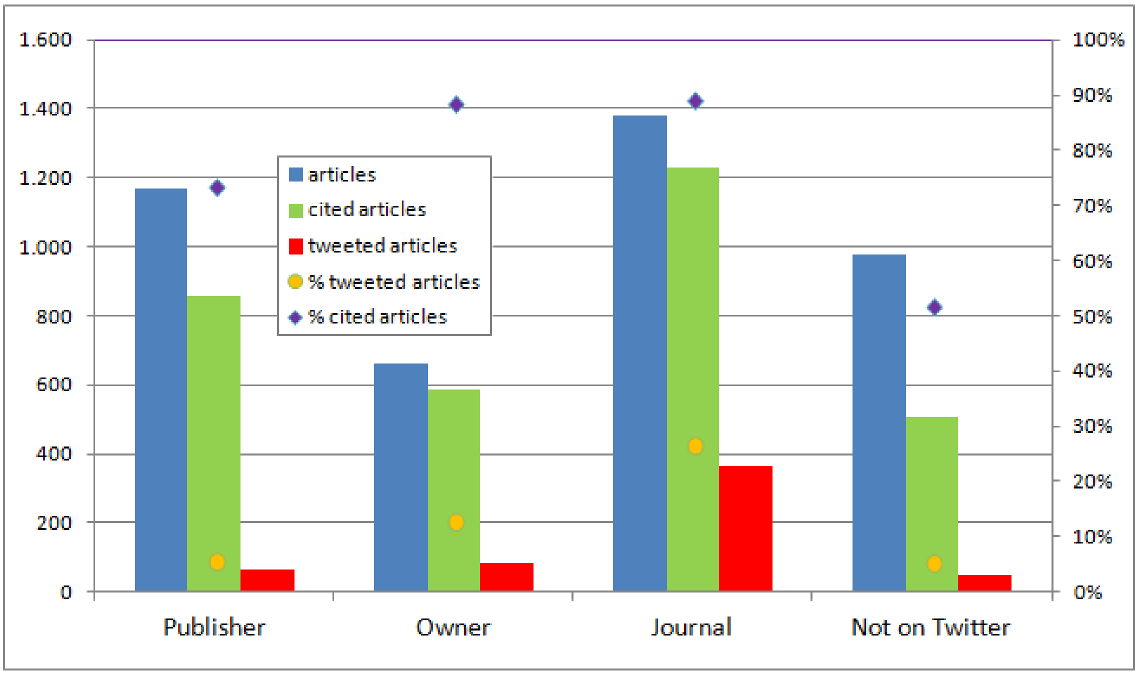

Figure 3. Number of articles, cited articles and tweeted articles by the journal Twitter account.

Figure 3 shows the distribution of analysed articles (4,176 papers) by the type of journal. 1,378 (33%) articles belong to journals with their own Twitter account, 1,170 (28%) to journals represented in Twitter through the publisher account, 661 (16%) papers from the journal's owner account and 977 (23%) items from journals without a Twitter account. According to the number of articles mentioned in Twitter, the proportion drops considerably because only 13% of articles are tweeted; a percentage a little higher than the observed in previous studies (Haustein et al., 2014; Zahedi et al., 2014; Meleki, 2014; Ortega, 2016). This difference could be due to many of these journals are part of the core of the academic publishing industry (Nature, PLOS, PNAS, etc.). Articles from journals with their own account are more tweeted (26%) than articles from journals with owner accounts (13%), publisher accounts (6%) and without accounts (5%). These percentages show that articles from journals with their own Twitter account are much more tweeted, more than double, than other articles from different journals. The proportion of cited papers is much higher in comparison with tweets. Articles from the journals with their own Twitter account (89%) and the owner account (88%) are the most cited, whereas articles from journals not registered on Twitter are the less cited (52%).

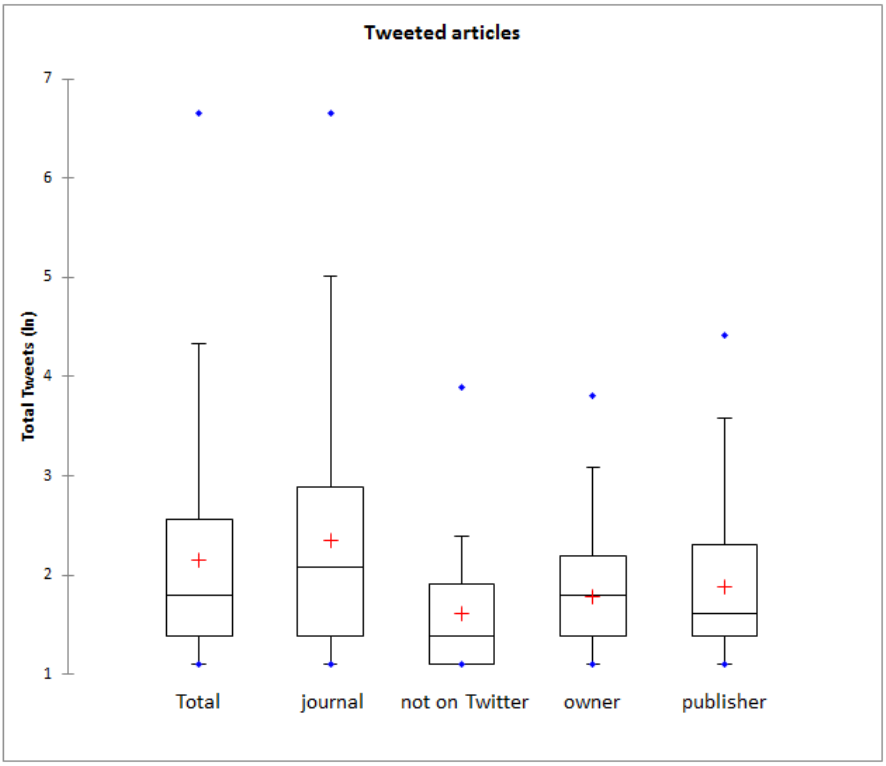

Figure 4. Box plot (log scale) of tweeted papers by the journal Twitter account.

Tweets	**journal**	**not on Twitter**	**owner**	**publisher**
journal	(±.11) 2.349	46% (< .0001)	32% (< .0001)	25% (< .0001)
not on Twitter	46% (< .0001)	(±.18) 1.61	10% (.121)	17% (.036)
owner	32% (< .0001)	10% (.121)	(±.11) 1.776	6% (.330)
publisher	25% (< .0001)	17% (.036)	6% (.330)	(±.19) 1.884

Table 1. Matrix with the Student's t-test for paired samples between each group (p-values) and percentage of variation between means. Diagonal shows the mean of each cluster.

Figure 4 plots the distribution of tweets per article by journal Twitter accounts and the Table 1 shows the result of the Student's t-test for paired samples and their signification levels (p-values). In addition, this table shows the percentage of variation between the means of each group. Results confirm that papers from journals with their own Twitter account are more tweeted than papers from other journals (p<.0001). In fact, the Student's t-test only finds statistically significant differences between the group of journals with their own Twitter account and the remaining groups. Only publisher group shows significant differences with regard to journals without a Twitter account at α=.05. Articles from journals with their own account are 46% more tweeted, on average, than articles from journals without a Twitter account, 36% more than articles from journals with owner account and 25% more than papers from journals with publisher account. The absence of differences among the other groups indicates that the other accounts do not have influence on the mention of articles. As it was said before, articles from publisher accounts show a slightly significant difference (p=.036) with respect to journals without Twitter account, being 17% more tweeted.

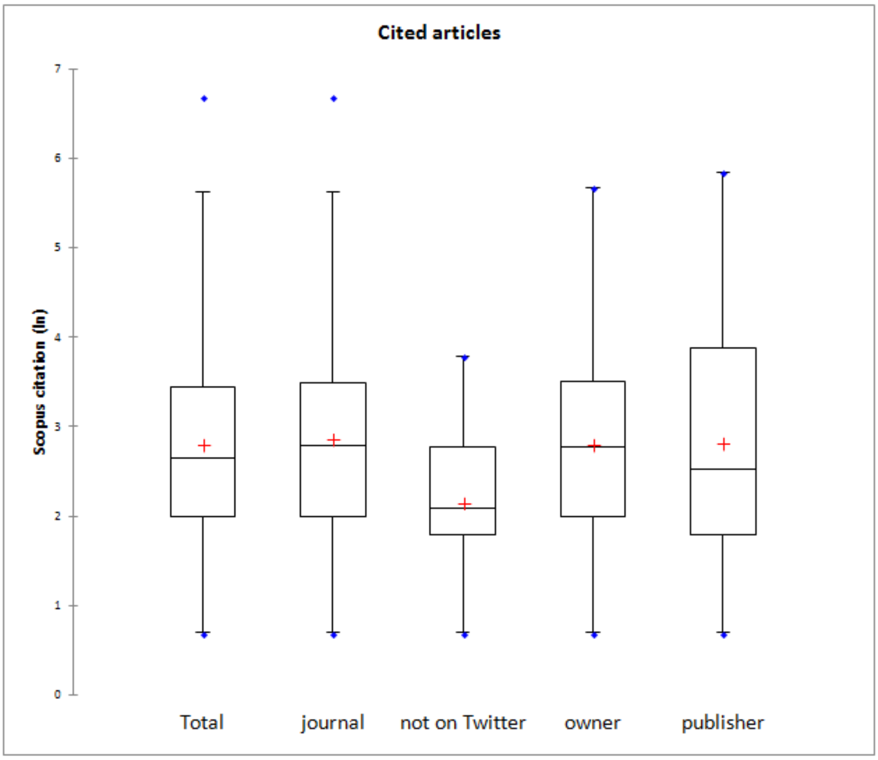

Figure 5. Box plot (log scale) of cited papers by the journal Twitter account.

Citations	journal	not on Twitter	owner	publisher
journal	(±.12) 2,86	34% (< .0001)	2% (.657)	1% (.841)
not on Twitter	34% (< .0001)	(±.25) 2,14	31% (< .0001)	32% (.003)
owner	2% (.657)	31% (< .0001)	(±.23) 2,81	.6% (.934)

publisher	1% (.841)	32% (.003)	.6% (.934)	(±.38) 2,82

Table 2. Matrix with the Student's t-test for paired samples between each group (p-values) and percentage of variation between means. Diagonal shows the mean of each cluster.

Figure 5 and Table 2 repeat the same analysis but now selecting only papers cited and tweeted simultaneously (501 articles, 91%). The purpose is to examine the influence of tweets on the citation of papers. Here, differences between groups are less significant and with less effect. Articles from journals without presence on Twitter receive fewer citations than papers from journals connected to Twitter. The most significant variation is found regarding papers from journal and publisher accounts, which receive 34% and 32% more citations than papers from journals without a Twitter account. However, if papers from journals with a type of Twitter account (i.e. journal, owner and publisher accounts) are compared, the t-test shows that there are no differences among them. This allows to state that the number of citations to a journal is independent of the different types of Twitter accounts.

5.2. Influence of Twitter activity on the dissemination and impact

The last objective of this study is to estimate the effect of the social networking metrics (i.e. number of tweets, followers and followings) of a Twitter account on the academic impact (citations) and dissemination (tweets) of research papers.

	Unstandardized Coefficients		Standardized Coefficients			95% Confidence Interval		
Model	B	Std. error	Beta	t	Sig.	Lower Bound	Upper Bound	R square adjusted
(Constant)	-1.216	.408		-2.981	.003	-2.023	-.409	
Followersbyyear_log	.470	.059	.575	7.961	.000	.353	.586	.326
1 Followersbyyear_log	.553	.070	.684	7.852	.000	.413	.694	.461
2 Tweetsbyyear_log	.198	.086	.393	2.303	.029	.022	.374	.125
3 Followersbyyear_log	.308	.118	.462	2.607	.015	.065	.550	.182

a. Dependent Variable: Tweets_year_log [1]Type=journal; [2]Type=owner; [3] Type=publisher

Table 3. Coefficients of the simple regression model for the number of tweets per year and by the journal Twitter account.

Table 3 shows the result of the regression analysis for the number of tweets per year. In all the cases, a stepwise method was applied, but only one variable was selected. This is because there was high collinearity among the Twitter activity variables. Followers is the only variable that is accepted in the general model and the marginal regressions. This means that the number of followers has a significant influence on the tweets that journals receive. In the event of owner account, the number of tweets is the most significant variable, but at the α=.05. This same happens with the regression by publisher account. Therefore, the coefficients of the general regression and the journal account are the only significant ones. These results suggest that the best way for journals to attract mentions is to increase their followers' network. Regarding the interpretation of the coefficients, an increase of 10% of followers might cause a growth of 4.7% of Twitter mentions. This relationship improves when only journals with their own account are considered. There, a 10% increase of followers could generate 5.5% of tweets. These coefficients show that the effort to attract tweets is very high because it is necessary to double the number of followers to obtain only the half of tweets. The adjusted R^2 also indicates that this fit is not very good and only in the best-case scenario (journal account) the effect is observable in the 46% of journals. In the event of owner and publisher accounts, their coefficients of determination show rather poor fits.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval		R square adjusted
	B	Std. error	Beta			Lower Bound	Upper Bound	
(Constant)	1.404	.259		5.423	.000	.894	1.914	
Followersbyyear_log	.283	.037	.424	7.550	.000	.209	.356	.177
1 Followersbyyear_log	.344	.052	.561	6.571	.000	.240	.448	.307
2 Followersbyyear_log	.254	.071	.383	3.570	.001	.112	.395	.135
3 Followersbyyear_log	.2	.074	.278	2.716	.008	.054	.346	.067

a. Dependent Variable: Scopus_year_log [1]Type=journal; [2]Type=owner; [3] Type=publisher

Table 4. Coefficients of the simple regression model for the number of citations per year and by the journal Twitter account.

Table 4 displays the coefficients of the regression analyses for the number of citations per year by Twitter handle. As in the previous analysis, due to the high collinearity among the variables, only simple regression models were constructed. The number of followers by year is again the only variable that influences the number of citations that an article receives. Here, only the coefficients of the general regression and the regressions by journal and owner accounts are statistically significant at the α=.001. The values of the coefficients are smaller than the observed ones in the analysis of the tweets. This informs us that the activity on Twitter has less influence on the citation impact. Even so, the interpretation of the model suggests, for the general regression, that a 10% increase of followers would only produce a 2.8% growth of citations for the general regression. This percentage is better for journal accounts (3.4%) and worse for owner handles (2.5%). These results clarify that journals need to develop a very strong presence on Twitter to slightly improve the research impact of their articles. In addition, this weak relationship between Twitter activity and citation impact is confirmed by the coefficients of determination (adjusted R^2), which show that this relationship only exists for 18% of the journals in the general case, and 31% of the journals with their own account.

6. Discussion

Results have shown that the proportion of tweeted papers is rather low, only 13% of the analysed papers were tweeted since 2013. This proportion is higher than the observed one in other studies (Haustein et al., 2014; Zahedi et al., 2014; Meleki, 2014; Ortega, 2016), where the proportion of tweeted articles does not surpass the 10%. In our study, this higher proportion could be due to the sample includes many top-tier journals (e.g. Nature, PLOS One, PNAS, etc.) and prestigious medicine journals (e.g. JAMA, The Lancet, NEMJ, etc.). Many of these journals have a great societal impact and therefore they could receive more tweets on average than other journals from disciplines less interesting to the public (Andersen & Haustein, 2015). Despite this, these results show that only a small fraction of the articles are being mentioned in Twitter. This could be a drawback for research evaluation at article level because most of the published articles go unnoticed on this social network.

The analysis of scholarly journals on Twitter, exploring their different types of accounts, has made possible the observation of different participation levels in the promotion of their articles. In addition, this study has shown that these different types of accounts could influence in different ways the visibility and impact of research papers. Results suggest that the best strategy to promote academic journals on Twitter is to have their own Twitter account, exclusively to disseminate the journal's content. Student's t-test has demonstrated that only journals with their own account show statistical differences with regard to the other types of account. Journals with their own account receive much more tweets on average than journals with owner (32%) or publisher (25%) accounts. According to citation differences between the Twitter accounts of journals, the results have clarified that there are no statistical differences between types of accounts, and the variation between the means are too small to confirm any significant difference. This allows to conclude that the number of citations that an article receives is independent of the Twitter account of its journal.

But, perhaps, the most important findings are about the active participation of journals in the dissemination of their articles. Results have indicated that the engagement of journals on Twitter increases the number of tweets that mention their articles, reaching on average up to 46% more tweets. According the influence of Twitter in the citation impact, findings have demonstrated that journals with their own Twitter account have 34% more citations than other journals without presence on Twitter. From a research evaluation perspective, this result might suggest that the journal activity on Twitter could affect the number of tweets and citations that their papers receive. However, these results confirm the relationship between dissemination and research impact, in which the broadcasting of research outputs influences the number of citations received. The more an article is spread over social networks, repositories, blog, news, etc., the more audience it reaches, increasing the likelihood of being cited by other researchers. As it was already observed by Ortega (2016), studying the role of authors in the spreading of their academic outputs on Twitter, the self-promotion of their articles via Twitter favours the dissemination and, indirectly, the research impact. This does not mean that the number of mentions in online social networks can be used as a proxy for research quality; but that these metrics should be understood as dissemination indicators. In this form, the impact of an article could result from the addition of dissemination and quality, although the weight of both components is not yet known.

In line with this idea, results from the regression analyses disclose that followers are the most important variable to increase the number of tweets and citations. This demonstrates that followers are the principal way to disseminate messages on Twitter. The more followers an account has, the more a message could be retweeted and therefore a broader audience could be reached. However, the effort to increase the number of tweets is high, because it is necessary to double the number of followers to get only the half of tweets (47%). In addition, this relationship is only statistically valid for 46% of the journals. This connection is even weaker with citations, because the increase of followers only produces a rise of 2.8% of citations. In addition, only 18% of journals are influenced by this effect. This result demonstrates that the citation pattern of research papers is related to Twitter mentions, but this link is rather weak and it is possible that this is a consequence of the diffusion rather than of the quality.

7. Conclusions

Three important conclusions could be extracted from the obtained results on the presence of scientific journals on Twitter and the dissemination (tweets) and research impact (citations) of their papers:

- Setting up one’s own account is the best way for journals to participate on Twitter because this decision improves the visibility of their articles, increasing the number of tweets and, in consequence, enlarging the chance of being cited.
- Articles published in journals with an own Twitter account are more tweeted than articles from other journals present on Twitter in a different manner or journals that are simply unaware of this network. This factor also influences the number of citations that papers receive, indirectly causing that journals with their own profile are more cited.
- The number of followers is the Twitter metric that most influences the number of tweets and citations that papers receive, although the effect of this variable is not very strong, being even less with citations.

8. Acknowledgments

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